Defining microclimates on Long Island using interannual surface temperature records from satellite imagery

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Overview: Micro-scale spatial variations in surface temperature, air temperature, and precipitation arise from local topography, urban development, and land cover differences, among other factors. These microclimates may influence spatial variations in vegetation productivity, soil types and profiles, species habitats, and geomorphology [e.g., *Finney et al.,* 1962; *Burnett et al.,* 2008; *Bennie et al.,* 2010]. Establishing microclimate boundaries may be useful in a variety of ecological, agricultural and environmental applications. Methods of spatially defining microclimates, however, are sparsely covered in the literature. This work uses a 5-year record of satellite imagery to identify spatial variations in interannual surface temperatures on Long Island. Daytime surface temperatures are a climate-related parameter; however, it is difficult to isolate the influence of climate from that of surface reflectivity and thermal conductivity on surface temperatures. Thus future work will also explore the application of these techniques to remotely-measured boundary layer temperatures as well as nighttime surface temperatures. These techniques may be applied to any region of interest.

Methods: Surface temperatures were obtained from the Moderate Resolution Infrared Spectrometer (MODIS) instrument aboard NASA's Earth Observing System (EOS) Terra spacecraft. EOS Terra is in a ~10:30 am/pm equator-crossing orbit with a repeat coverage time of ~1 day for any region. MODIS radiance data is collected in 36 channels between 0.4 and 14.5 µm. Radiance from channels 31-32 (10.7-12.2 µm) are converted to surface temperature using an estimate of emissivity derived from the MODIS Land Cover Product [*Strahler et al.,* 1999]. Surface temperatures have an accuracy of better than 1°C for surface temperatures between -10-50°C [*Wan et al.,* 2004]. In addition to individual image products, the MODIS instrument team generates 8-day surface temperature composite images for any given region, at a spatial resolution of 1 km per pixel [*Wan,* 2009] (**Figure 1**). The advantage of composites is that cloud-covered pixels are excluded from the average.

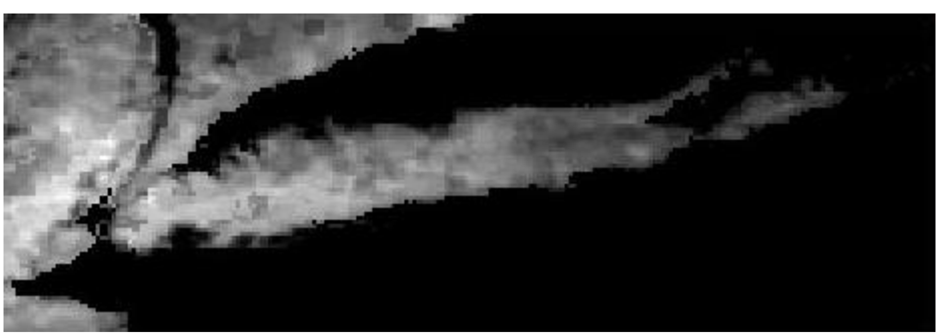

Figure 1. Example of MODIS land surface temperature composite image, acquired June 2000. Temperature range is 7°C to 29°C (black to white).

Over 200 8-day composite images of daytime surface temperature spanning the time period of January 2005-2010 were obtained. Images were projected and compiled into a 3-dimensional data cube, where the x and y dimensions are longitude and latitude, and z dimension is time. Arranged in this manner, each pixel contains a "spectrum" of surface temperature vs. time. In this work, we searched for pixels with similar interannual temperature spectra. To find locations with similar temperature spectra, the ISODATA (iterative self-organizing data analysis technique) unsupervised spectral classification method was used. This technique relies on minimum distance cluster analysis and works within user-defined constraints, including a target number of clusters, minimum number of pixels assigned to a class, and a minimum distance threshold whereby clusters are split or merged [*Ball and Hall*, 1965; *Anderberg*, 1973]. For the technique to produce meaningful results, constraints on the number of allowable classes must be determined by the analyst. Here, the appropriate number of classes is established by two criteria. First, the average temperature spectrum of each class must lie outside of one standard deviation from the global mean. Second, we used principal components analysis (PCA) to estimate the number of independently varying components in the scene. Determining the appropriate number of classes relies on an iterative approach, where the target number of classes is incrementally increased and the surface temperature distributions and average temperature spectra are evaluated against the criteria described above. Too few classes will not produce average spectra that are distinct from the global mean, while too many classes will force the separation of regions that differ insignificantly from each other.

<u>Preliminary Results</u>: Results from PCA transforms suggest that the appropriate number of classes should range between 6 to 9. With PCA, each principal component band identifies a progressively less significant independently-varying component. Thus the first few PC bands should show some degree of spatial coherence, whereas the lower PC bands tend to exhibit high spatial frequency with little control from regional surface trends. For the data analyzed in this work, PC bands 1-9 show reliable spatial coherence, particularly in the first 6 bands (**Figure 2**).

The ISODATA classification method was run allowing a maximum of 9 clusters. For this scene, water bodies form one of the clusters; thus land surfaces are limited to 8 classes (**Figure 3**). As expected, most of the class distributions are strongly controlled by urban development associated with New York City. However, at least one of the classes appears to relate to sea-side geographic location, either due to thermal conductivity or reflectance properties of sand, or to seaside climate.

Average spectra from each class in **Figure 3** were examined in order to understand the interannual or seasonal temperature differences that led to the spatial classification. From these plots (**Figure 4**), it appears that the most significant difference between Long Island regions is in summertime surface temperatures. Winter temperatures for all classes are largely similar. Class 3, which is restricted to urban areas, exhibits the highest summer temperatures, whereas Class 1, also restricted to urban areas, exhibits the lowest summer temperatures. The differences between class 1 and 3 may be related to the difference in shadow-producing structures like tall buildings, or to differences in vegetative cover. Higher spatial resolution images such as those from the Landsat Thematic Mapper are needed to investigate these differences. The average spectra for Classes 4, 5 and 7, which fall in eastern Long Island and Connecticut, are not statistically separable from one another, and should be recombined. Classes 1, 3 and 8, which largely fall in

Manhattan but also include seaside surfaces, exhibit more short-term temporal variability than the other classes. The cause for this variability is unclear.

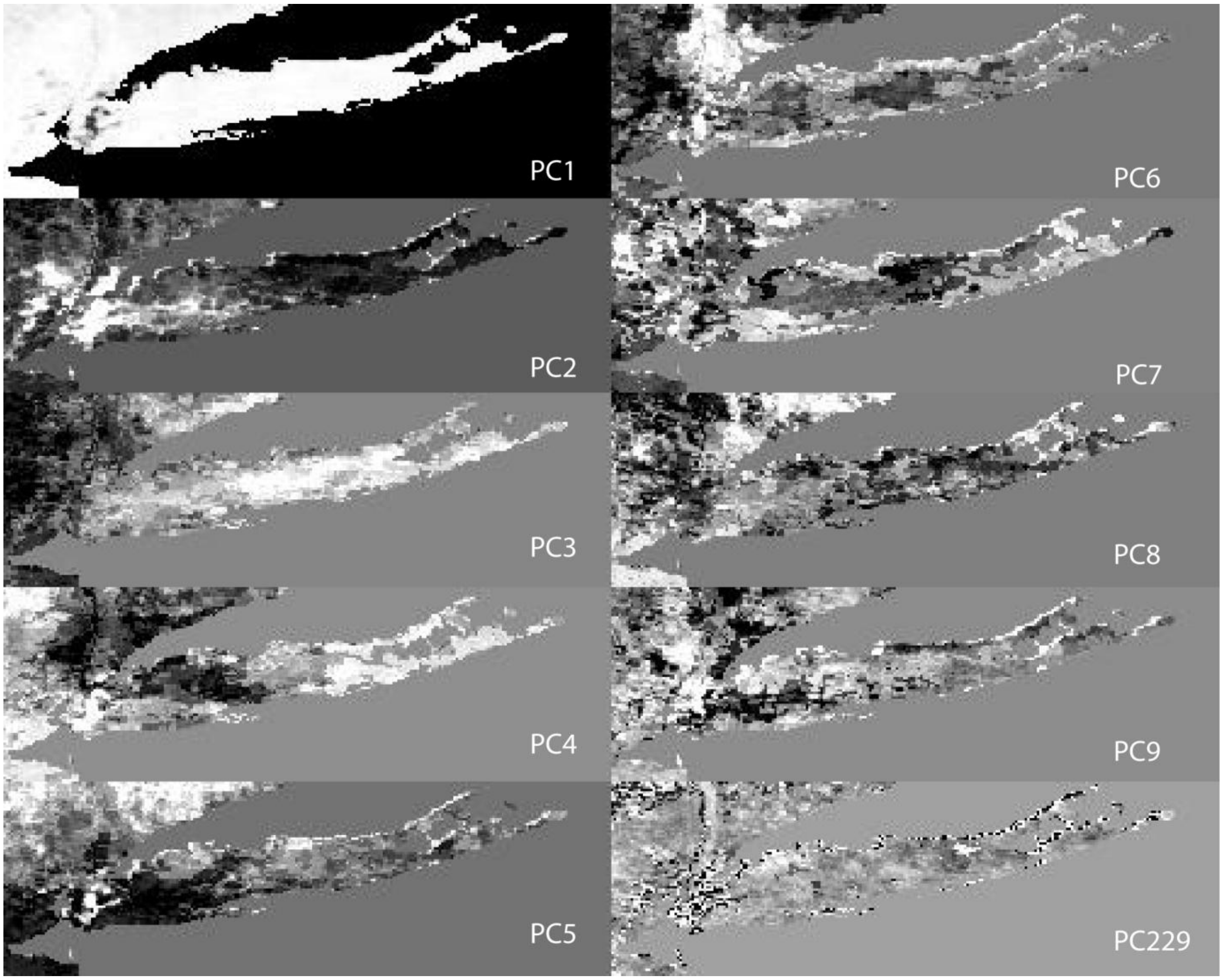

Figure 2. Principal component (PC) bands 1-9 and band 229 for comparison. High spatial frequency, as exhibited in band 229, suggests that the principal component identified is not a real surface component. Bands above ~PC6-9 start to exhibit this behavior.

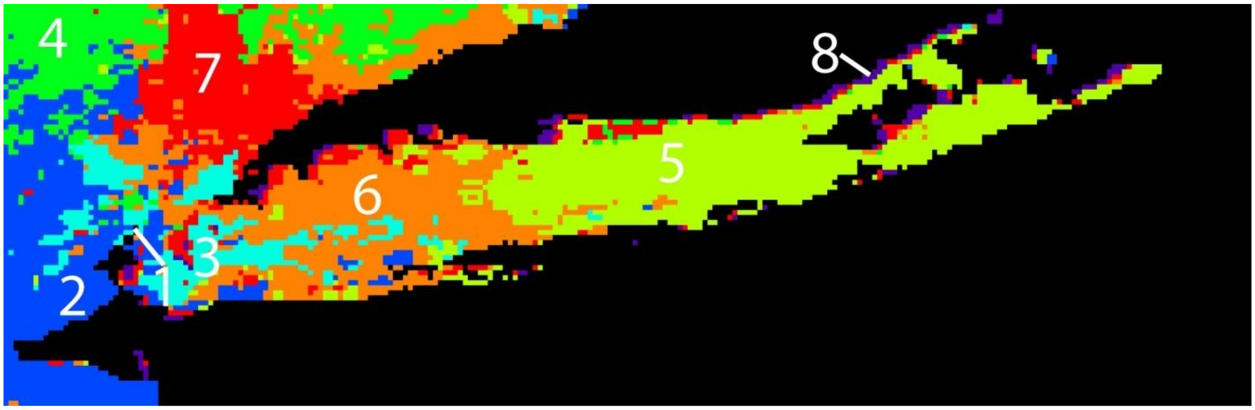

Figure 3. Classification map derived from interannual surface temperatures.

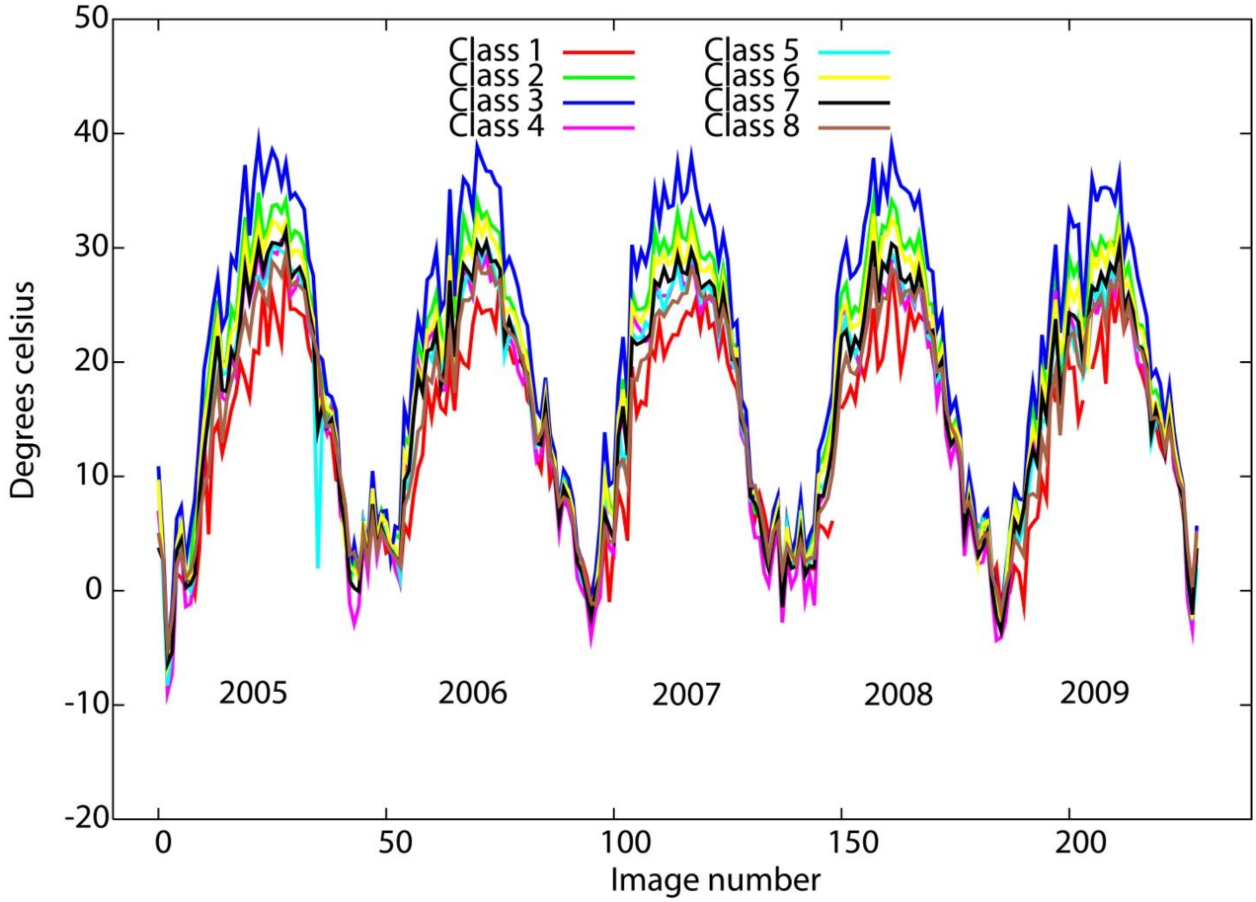

Figure 4. Average temperature spectra from the eight clusters identified using unsupervised classification.

<u>Conclusions and Future Work:</u>

The preliminary work presented here suggests that the classification and principal component techniques, which are usually applied to spectral reflectance data, may also be useful for defining microclimate regimes based on seasonal or interannual temperature records. Future work will include analysis of Landsat temperature records, which have a 60-90 m/pixel spatial resolution and span a longer time period, as well as analysis of remotely derived near surface air temperatures. Spatial distributions of microclimates derived from this work can be compared with spatial trends in vegetation productivity (derived from remotely measured spectral information) and soil cover. Comparisons with land use/land cover maps may also help to isolate the primary controls (e.g., land cover, meteorological phenomena) on microclimates in this region.

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